Frigatebird behaviour at the ocean-atmosphere interface: integrating animal behaviour with multisatellite data

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SUPPLEMENTARY MATERIAL

Birds 3-D trajectory

**ESM Figure S1.** 3-D trajectory of bird (tag # 542309082) in its 40 hours-long flight off Europa island. Figure 1 displays its projections in terms of altitude vs time and horizontal coordinates.
Classification of frigatebirds behaviour

We exploited the information about the altitude of birds along a trajectory to assign to each position on the sea surface a behaviour of the bird when it is found over that location. Our algorithm is based on previous observations of frigatebirds' behaviour [28, 26], which we translate into criteria on the vertical velocities. We have chosen such criteria in order to perform the analysis of all the trajectories (for a total of 316 flight hours) automatically, and we adjusted the analysis windows filtering out possible changes in behaviour on a frequency too high with respect to the environmental inhomogeneities that we are able to detect from remote sensing.

As a first step, spikes have been removed from the time series. These correspond to inevitable errors in the GPS vertical positioning, but they can be easily recognized as outliers by comparison with the nearby positions, since they correspond to unrealistically big vertical displacements (corresponding to vertical velocities larger than 3 m/s [26,21]). Then, we have interpolated the birds trajectories with a one-minute time step in order to fill the holes in the data points due to spike filtering. Finally, we have then applied a classification algorithm to the interpolated trajectories and subsequently assigned to each data point the behaviour of the closest point in the interpolated trajectory.

Let us now detail the classification criteria for the 5 different behaviours used in the manuscript.
1. **Low Flight.** Points whose altitude is below 20 meters. The threshold of 20 meters was chosen sufficiently large to accommodate for possible errors in the altitude measure by GPS, that appeared to be particularly noisy close to the sea surface (including also negative values, that were eliminated from the database). All the following criteria are applied only to points whose altitude is larger than or equal to 20 meters.
2. **Fast Descent.** Points such that all points of a window centered in that focal point have negative vertical velocity and have an average vertical velocity inferior to -0.05 m/sec. We chose a 9-point window (corresponding to about 9 minutes) in order to match the typical duration of peaking events and thus exclude exceedingly fast oscillations of the altitude recording, that are irrelevant for our analysis and more error-prone. We corrected for the conservative nature of this classification, that excludes extreme points of a descent because they are close to points with positive velocity, by enlarging the interval for this behaviour of 2 points.
3. **Slow Descent.** Points with absolute value of the vertical velocity smaller than 0.05 m/sec and such that all points of a 9-point window centered in that focal point have negative vertical velocity.
4. **Slow Ascent.** Points such that the average vertical velocity in a 21-point window is between 0.01 and 0.22 m/sec. This includes cases where climbing occurs through a winging alternation of ups and downs.
5. **Fast Ascent.** Points such that the average vertical velocity in a 21-point window is larger than 0.22 m/sec. The choice of not imposing that the velocity has to be positive in all the window corresponds to the observation that climbing occurs in a more discontinuous way with respect to descent, and that even long-term ascents are often interrupted by short descents. The 21-points window (corresponding to a time span of 21 minutes) and the threshold of 0.22 m/sec have been selected so that the class of FA included all the long-term climbing events that were recognizable by eye. Analogously with the case FD, in order for the classification to be consistent with the visual recognition, we have enlarged the windows of FA of 5 points.
Behavioural patterns along a trajectory and environmental parameters

ESM Figure S2. Azimuthal projection of the trajectory of Figure S1 with behavioural patterns (Low-altitude Flight, magenta; Fast Descent, blue; Slow Descent, red; Slow Ascent, green; Fast Ascent, cyan); (A) azimuthal projection of the trajectory superimposed to finite-size Lyapunov exponents (FSLEs) fronts (FSLE> 0.1 day\(^{-1}\)); (B) azimuthal projection of the trajectory superimposed to SST (range 21\(\pm\)25°C); (C) azimuthal projection of the trajectory superimposed to wind divergence (range -4\(\pm\)4 sec\(^{-1}\)); (D) azimuthal projection of the trajectory superimposed to crosswind SST gradient (range -4\(\pm\)4°C m\(^{-1}\)). All the physical data have been regridded with a resolution of 1/10
degree.

Analysis of frigatebird behaviour with respect to the crosswind SST gradient diagnostics

By computing the crosswind-SST gradient [38,39], vertical wind patterns can be mechanistically related to thermal fronts and to the direction of horizontal winds. The crosswind SST gradient is correlated to QuikScat divergence, however only on a large scale and in a climatological sense (see the discussion of error bars in Fig. 4 of ref. [39]). We test whether vertical winds thus directly related to thermal gradients affect frigatebird behaviour. The analysis shows no significant association of different behaviours to regions of upwards winds (Fig. 2D). This could be due to the accumulation of errors in SST and wind fields when combined together at this resolution and/or the fact that, at the (sub-)mesoscale, the dominant mechanism driving vertical winds exploited by frigatebirds is not the crosswind SST gradient, but other contingent phenomena such as for instance convection induced by clouds [26].

**ESM Figure S3.** Behavioural patterns observed on (47% of the flight time) and outside the regions of ascending vertical wind identified by negative crosswind SST gradient.
**Bootstrap**
The difference between the frequencies observed in and outside the physical structures may arise simply because we have a finite number of independent observations and not because there is an association between specific behaviours and environmental features. In order to test the significance of our results against this null hypothesis, we generate a large number of realisations of random repartitions of the behaviours over the whole trajectory. Such distribution has a non-zero standard deviation due to the fact that there is only a finite number of independent observations.

We generate 1000 synthetic datasets by randomly reshuffling the behaviours irrespective of their location along the trajectory, and then compute the fractions of time in each behaviour conditioned to being on or outside the target (sub-)mesoscale region. This way, we obtain for each behaviour a Gaussian distribution of fractions centered around the frequency of occurrence of that behaviour in the whole trajectory. The number of realizations (1000) has been chosen in order to ensure the statistical stability of such distribution. The standard deviation of the fractions inside and outside the target region is a function of the number of independent observations falling in that region, that we compute as the ratio between the number of actual measures and the number of correlated measures. Notice that the standard deviation can be thus different for the fractions on and outside the target region: regions with a smaller number of observations will have a larger associated error bar.

In order to compute the number of independent observations we divide the total number of samples by the autocorrelation length of frigatebird behaviours, which provides the typical time over which a behaviour is maintained. In order to estimate this quantity we compute the correlation in behaviour type at neighboring points along all trajectories.

We consider that this time (potentially smaller even of the observation interval of 2 minutes) is upper bounded by the time length over which the birds vertical velocity looses correlation. ESM Figure S4 shows the autocorrelation index calculated separately over the 9 trajectories examined in this study: the correlation drops to zero at an interval of at most 4 subsequent samples (corresponding to 8 minutes).

![Autocorrelation index](image)

**ESM figure S4.** *Autocorrelation index of the vertical velocity in the 9 trajectories considered in the analysis. The trajectory number is indicated in the legend. As a reference, the trajectory used as an illustrative example is trajectory number 7.*
We stress here that this estimation is a worst-case scenario: birds are likely able to change their behaviour on a much faster timescale. Therefore, the error bars shown in Figure 2 have to be taken as upper bounds of the real uncertainty.